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The importance of volunteered geographic information for the validation of flood inundation models

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ABSTRACT

Two dimensional flood inundation models capable of simulating complex spatially and temporally differentiated floodplain flows are routinely used to model and predict flooding. However, advances in modelling techniques have not been matched by improvements in model validation. Validation of flood models remains challenging due to a lack of available spatially-explicit data; traditionally measured data and validation approaches reveal little about the ability of a model to simulate the complex dynamics of floodplain flows, including the pathways, timeline, and impacts of an event. In this paper we propose a novel method for the validation of hydraulic models of flooding using quantitative and qualitative Volunteered Geographic Information (VGI). This method uses VGI data to enhance traditionally measured validation data by reconstructing the observed dynamics of a flood, allowing validation of the temporal and spatial simulation of these dynamics. We illustrate the method using a case study from Corbridge in the northeast of England, using VGI collected through participatory research with people affected by severe flooding in 2015. The results of the study demonstrate that VGI data can be used for the effective reconstruction of flood event dynamics. The results also reveal that the proposed validation approach is able to identify underperformance in the model's simulation of event dynamics not evaluated by standard global performance measures. Such a lack of evaluation can have adverse consequences where dynamic model outputs are used locally to influence floodplain management. As a result, we propose a new framework for model validation, adopting a pragmatic and flexible approach to examining event dynamics using a diverse range of data.

1. Introduction

Flooding is one of the most serious environmental hazards globally, with flooding the cause of almost 50% of all economic losses resulting from natural hazards (Munich Re, 2013); and losses are likely to increase under climate change as flooding is exacerbated (Hirabayashi et al., 2013; Reynard et al., 2017). The need to better understand current and future flood risks has led to a significant rise in the use of predictive numeric models to understand river processes, including flooding (Bates and De Roo, 2000; Hunter et al., 2007; Lane et al., 2011a; Parkes et al., 2013). The availability of high quality, spatially-distributed data on river environments (Cobby et al., 2003) means two dimensional models, capable of explicitly simulating complex, spatially and temporally-differentiated floodplain flows are now a standard approach in many fields, including the insurance industry (Bates and De Roo, 2000; Bradbrook et al., 2004; Hunter et al., 2007; Néelz and Pender, 2013; Teng et al., 2017). However, improvements in data, and advances in numerical modelling techniques, have not been matched by improvements in the validation of these models; the process by which we can assess whether our models agree with observations (Refsgaard and Henriksen, 2004). Established approaches to validation are typically spatially or temporally limited in scope by the availability of accurate datasets.

This paper seeks to address gaps in our existing data and practices of model validation. Using a case study from northeast England, we propose a new approach, which builds on existing statistical methods of comparison against observed data. We demonstrate that, by exploiting diverse, volunteered and crowd-sourced datasets, we can both spatially and temporally reconstruct the key dynamics of flood events. The approach demonstrates how alternative data-sources can be used to enhance existing data, providing information on flooding processes for which traditionally regarded data is rarely available. Finally, the approach offers a more holistic validation of the complex dynamics of floodplain flows, including the pathways, timeline, and impacts of events.

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2. Application of volunteered geographic information in hazard assessment

2.1. VGI data in disaster risk reduction

Paucity of measured data on disasters, including floods, is common in the field of Disaster Risk Reduction (DRR). To address this issue, research has explored the use of non-standard, unscientific datasets derived from local communities within a disaster zone (Goodchild and Glennon, 2010). One data source being explored within DRR research is Volunteered Geographic Data (VGI: (Haklay et al., 2014)), defined as 'the widespread engagement of large numbers of private citizens, often with little in the way of formal qualifications, in the creation of geographic information' (Goodchild, 2007, p. 212). VGI datasets include any geo-located information on a disaster, and can comprise a diverse range of data including personal accounts, photographs and videos, and crowd-sourced measurements (Hung et al., 2016; McDougall, 2012; Triglav-Cekada and Radovan, 2013).

The use of VGI datasets has been demonstrated across a wide range of studies of hazard events (for systematic reviews of the current research base see Granell and Ostermann, 2016; and Klonner et al., 2016). For floods, the use of VGI data has been demonstrated across a range of applications. For instance, McCallum et al. (2016) utilised VGI to improve the availability of pre-event data on flood vulnerability in data-sparse regions, demonstrating how crowd-sourced information can enhance mapping for emergency responders after disasters. A number of studies have also explored the potential for collecting VGI datasets to inform real-time disaster response. For example, Wan et al. (2014) at a global scale, and Degrossi et al. (2014) and Horita et al. (2015), both working at city scale in Brazil, demonstrated cloud-based systems for the collection and processing of VGI flooding data. These systems synthesised diverse flooding datasets, providing real-time information for emergency response and developed a long-term database of information on historic floods. VGI has also been used in the post-event phase: Schnebele and Cervone (2013) and Triglav-Cekada and Radovan (2013) utilised VGI flooding imagery collected after the event to improve flood maps derived from satellite imagery. Such research demonstrates how the VGI data can provide spatially distributed information on even large flood events, and how it can also be used to validate remotely-sensed hazard maps at a local scale.

While these examples demonstrate the emerging, widespread application of VGI for disaster preparedness and response, they also demonstrate how limited and fragmented the use of VGI data is for many applications; reflecting the non-standard nature of the data. McCallum et al. (2016) use only participatory mapping for their vulnerability assessment, whilst Schnebele and Cervone (2013) and Triglav-Cekada and Radovan (2013) use only imagery for their flood mapping analysis. Wan et al. (2014), Degrossi et al. (2014), and Horita et al. (2015) collected a wider range of data, including citizen reports of flooding, but highlighted significant problems utilising such diverse datasets which cannot be automatically processed. Other criticisms of VGI datasets often focus on issues of data validity or the difficulties of assessing data quality in the absence of traditionally-measured data sources (Hung et al., 2016; Muller et al., 2015). As a result, many studies use collection of VGI data as an adjunct to traditional data, rather than as a source of data in its own right or as a standalone method for the creation of new knowledge about specific hazards such as flooding (Usón et al., 2016).

2.2. Emerging practices of engagement

In contrast to the VGI projects noted in Section 2.1, citizen science and citizen observatory programmes represent moves towards establishing new practices of geo-spatial knowledge co-creation. These efforts are driven by the need for greater public participation in environmental decision-making (National Research Council, 2008) laid out in the Aarhus Convention (Lee and Abbot, 2003) and the European Floods Directive (Wehn et al., 2015). Citizen science and citizen observatories have been demonstrated across a range of disciplines including flooding and hydrology (Lanfranchi et al., 2014; Muller et al., 2015; Ruiz-Mallén et al., 2016; Starkey et al., 2017), and research has begun to demonstrate how citizen-led, locally collected data can provide valuable information for enhancing our understanding of catchment processes and planning catchment interventions (Starkey et al., 2017). In contrast to the often *ad-hoc* collection of VGI data, citizen science typically involves engaged and trained participants and rigid data collection frameworks to help overcome issues of data validity (Wiggins and He, 2016).

However, an issues arises: flood events, in common with other disasters, represent situations in which data can often only be collected in an *ad-hoc* fashion, as the presence of local volunteers able and willing to collect data cannot be guaranteed (Starkey et al., 2017). This is particularly relevant as citizen science programmes are often limited to small numbers of participants (Baruch et al., 2016), meaning drop-outs during an event would have a greater impact on the data collected. Efforts therefore need to be made to understand how we can integrate the opportunities for large scale engagement represented by VGI with the opportunities for local participation, and the improvements in data quality, represented by citizen science. Studies have begun to explore how integrating citizens into activities beyond simple data collection can improve engagement and data quality, for example see Starkey et al. (2017), but in the context of flooding this field is still in its infancy. However, there is obvious potential for a more integrated approach between large scale VGI data collection and the more locally focused nature of citizen science (see Brandeis and Carrera Zamanillo, (2017) for further details).

2.3. Integrating citizen data into the validation of flood inundation models

One situation which potentially offers the opportunity to integrate citizen science and VGI in this way is in the construction and validation of numerical flood inundation models of flood-affected communities. Flood inundation modelling forms a cornerstone of flood risk assessment (Bates and De Roo, 2000; Hunter et al., 2007; Lane et al., 2011a; Parkes et al., 2013). It informs almost all flood management activities, from monitoring and warning systems (Nester et al., 2016), to evacuation planning (Simonovic and Ahmad, 2005) and emergency response (Coles et al., 2017), to the design and construction of future developments (Pappenberger et al., 2007a). However, at present, flood modelling is primarily an expert-led activity with little or no citizen involvement (Lane et al., 2011b).

The established approach to validating inundation model outputs is to match available historical data to simulated outputs (Pappenberger et al., 2007a). The goodness-of-fit between predicted and observed river levels can be assessed using statistical best-fit techniques such as Nash-Sutcliffe Model Efficiency (NSME) (Nash and Sutcliffe, 1970) or Root Mean Square Error (RMSE) (Altenau et al., 2017). Similarly, point-in-time global flood extents can also be assessed using binary performance measures such as the Critical Success Index (C), which compares the extent of simulated inundation to the observed inundation (Wing et al., 2017). What tests are undertaken is dependent upon data availability. In-channel river level data is a source of historical information commonly available in medium and large catchments (Hunter et al., 2007; Parkes et al., 2013). To examine out of bank inundation, high resolution aerial and satellite imagery (Renschler and Wang, 2017), multiband remote sensing such as LANDSAT (Fernández et al., 2016; Jung et al., 2014), or other sensors such as Synthetic Aperture Radar (García-Pintado et al., 2013; Pappenberger et al., 2007b; Wood et al., 2016) can all be used. Studies have also demonstrated the usefulness of ground observations of wrack and water marks in reconstructing maximum inundation extents and levels, (Neal et al., 2009; Parkes et al., 2013; Segura-Beltrán et al., 2016). However, collection of this latter form of flood inundation evidence typically requires post-event surveys which are time and resource consuming and often yield spatially limited results (Segura-Beltrán et al., 2016).

The validation of model outputs is therefore constrained by data availability to being either spatially or temporally limited: gauged river levels may record levels throughout an event but are limited to discrete locations; whilst remote sensing can provide spatially extensive information on inundation but only at discrete time points. Consequently, established statistical techniques for model validation have been unable to assess the effectiveness of models in simulating both spatial **and** temporal event dynamics (Hunter et al., 2007). These dynamics include the pathways which water takes across the floodplain, the flood timeline, and local variation in flood impacts; all of which are capable of being simulated in detail by current 2D inundation models (Teng et al., 2017). This disparity between the complexity of current inundation models and the relative lack of data against which to test them represents an opportunity to integrate citizen-collected data into existing, expert-led practices of knowledge creation. Thus far however, there has been little exploration of this issue.

3. Methods

In this research we build on the methodology used by Smith et al. (2012) by demonstrating how VGI data should be used more routinely for model validation as a dataset in its own right. Smith et al. (2012) provide a demonstration of the use of a diverse VGI database to construct and validate a model of coastal flood defence overtopping. They utilise VGI to build the model, by using locally recorded locations of flood defence overtopping as point inflows into the model domain. They also validate its outputs, reconstructing the observed flood extents and depths at properties using historical photographs and media accounts. However, the approach demonstrated was limited by the data used, which was confined to imagery and records of depth at specific locations. By examining only modelled extent and depth, the method provides a spatial but not a temporal validation. The resultant model cannot examine the functioning of the model in simulating flood dynamics in more detail, nor does the study explore how VGI could be used more comprehensively. This is reflected in Smith et al.'s conclusion that the data used represented "*useful **corroborating** evidence for the performance of the model"* (p. 43), after a more traditional validation using available measured data.

In this study we develop an experimental validation methodology which uses a wide range of data potentially available through VGI and participatory research approaches to examine different aspects of a simulation output. To demonstrate the method we use a database of VGI to reconstruct in detail a severe flood in the northeast of England, and use a VGI-based flood reconstruction to validate the outputs of a 2D flood inundation model of the event. Finally, we compare the outputs to more established methods of validation to demonstrate the success of the method.

3.1. Model build

We utilised the flood inundation model LISFLOOD-FP to produce simulated flood event outputs for our case study. LiSFLOOD-FP is a 2D finite difference model developed specifically to utilise high resolution topographic data to simulate floodplain dynamics (Bates et al., 2010; Hunter et al., 2005; Neal et al., 2012, 2011; Bates and De Roo, 2000). Although we used LISFLOOD-FP here, the validation approach developed should be considered generic, and is designed to be applicable to any 2D model that predicts dynamic floodplain inundation. The principle data requirements for the model are outlined in Table 1.

3.1.1. The case study: The 2015 Corbridge flood

The test case used in this study is the market town of Corbridge, located in the Tyne Valley in the northeast of England (Fig. 1). Corbridge was chosen to develop and test the experimental validation because of its recent history of severe flooding and the way its population were already engaged with ongoing flood research (Rollason et al., 2018).

Corbridge experienced extensive flooding when Storm Desmond resulted in record rainfall across areas of the north of England (Barker et al., 2016) on 5th December 2015. The flood, an event with a return period estimated to be between 100 and 200 years (Marsh et al., 2016), overtopped the flood defences at Corbridge, and inundated 70 properties on the south side of the River Tyne (Environment Agency, 2016).

Using LiSFLOOD-FP a model of the River Tyne was constructed, extending for approximately 30 km, with Corbridge situated approximately half way down the modelled reach. Fig. 1 shows the modelled reach and the main data used are discussed in Table 1. To predict the December 2015 flood event, the model was run for a 72 h period starting at 12:00 on Friday 4th December continuing until 12:00 on Monday 7th December. This period covered both the rising and falling limbs of the main hydrograph at Corbridge. Simulation results were generated for every 15 min period, predicting flood depths, flood velocity, and time of inundation.

3.2. Validating the model outputs using established approaches

Initial verification and calibration of the model was undertaken during the model build. The mesh resolution independence of the model was verified by testing against DEM resolutions of 5.0, 7.5, 10.0, and 20.0 m (Hardy et al., 1999; Horritt and Bates, 2001). The model was further calibrated against floodplain friction values, which were estimated from Chow (1959) based on satellite imagery and field visits. Differential friction values were applied to the channel of the Tyne and the main floodplain, with the area of the channel delineated based on satellite imagery. Manning's values for floodplain friction between 0.02 and 0.06 ($m^{1/3}\,s^{-1}$) and channel friction values between 0.03 and 0.07 ($m^{1/3}\,s^{-1}$) were used in the model calibration runs, validation of which was undertaken using established statistical approaches. Validation was also undertaken on the calibrated model as a baseline against which to test the effectiveness of the experimental methodology.

Two datasets were available for the validation using established statistical techniques: gauged river levels and observed flood extents for the estimated maximum extent. Gauged river levels were validated using both Nash-Sutcliffe Model Efficiency (NSME) and Root Mean Square Error (RMSE) (Altenau et al., 2017). Maximum flood extents were validated using the Critical Success Index (C) (Wing et al., 2017; Wood et al., 2016), sometimes referred to as the 'fit statistic' (Sampson et al., 2015). C tests the proportion of wet observed data that is replicated by the model on a per-pixel basis, accounting for both over- and under-prediction:

$$C = \frac{M_1O_1}{M_1O_1 + M_0O_1 + M_1O_0}$$

where M is the modelled outcome and O is the observed outcome, and 1 or 0 represents pixels that are either wet or dry. C can range from 0 (no match between simulated and observed inundation) to 1 (perfect match between simulated and observed inundation).

3.3. Developing a new solution for validating inundation models

3.3.1. The Volunteered Geographic information database

Participatory research in Corbridge was undertaken with the community at to develop a VGI database of local knowledge and experiences of the December 2015 flooding event. As part of wider participatory work being undertaken at Corbridge (see Rollason et al., 2018) we carried out two participatory mapping workshops with 10 research participants, and five individual walking interviews, after Evans and Jones (2011). Discussions and interviews were un- or semi-structured in nature (Dowling et al., 2016), with participants being encouraged to lead the discussion and discuss their own knowledge and experiences.

Table 1
The principle data requirements of the LiSFLOOD-FP model and the data used in the construction of a model for this study.

Model component	Data required	Data Used in the study
Topography	Pre-processed, 'bare-earth' raster grid of topography with buildings and vegetation removed	Environment Agency 2 m horizontal resolution 'bare earth' LiDAR data, resampled using averaging technique Structures, e.g. bridges and flood defences, added to the DEM prior to inclusion in the model
Inflow conditions	Stage or discharge inflows	Point inflows from Environment Agency gauging stations at 15 min temporal resolution
Outflow conditions	A downstream boundary derived from either gauged river levels or a free flow boundary	Free flow boundary using slope calculated from local DEM values
Floodplain friction parameters	A raster grid representing Manning's 'n' values for different landcover classes	Values estimated from Chow (1959) based on satellite imagery and field visits

During the mapping workshops participants were encouraged to locate their knowledge on blank maps of the study area, for example observed locations of defence overtopping or pathways of flood water flow. Walking interviews were also participant-led following either the natural go-along (Kusenbach, 2003), or participatory walking interview (Clark and Emmel, 2008) models. Spatial data were recorded either directly into GIS or onto paper maps for later digitisation. Verbal discussions were recorded and analysed by adopting a grounded theory approach (Charmaz, 2011), combining both the audio recording and visual representations (Knigge and Cope, 2006). Information provided in anecdotal accounts was triangulated with digital images and video taken during the event and collected during the participatory process.

The information were used to produce an extensive database of how the flood occurred (Table 2). Most of the data was collected from the local community but it was augmented by (non-georeferenced) footage from an unmanned aerial vehicle (UAV) identified on news footage immediately after the event, and collected by a local UAV enthusiast.

3.3.2. Using the VGI database to reconstruct the dynamics of a severe flood

During validation it is necessary to establish the main dynamics of the flooding event for which the model is being validated. To do this, we divided the VGI data into three information categories:

1. *Pathways* – data which provided information on the movement of flood water through the study area, including areas of overtopping and principle flow directions.
2. *Impacts* – data which provided information on the maximum extent of the flooding.

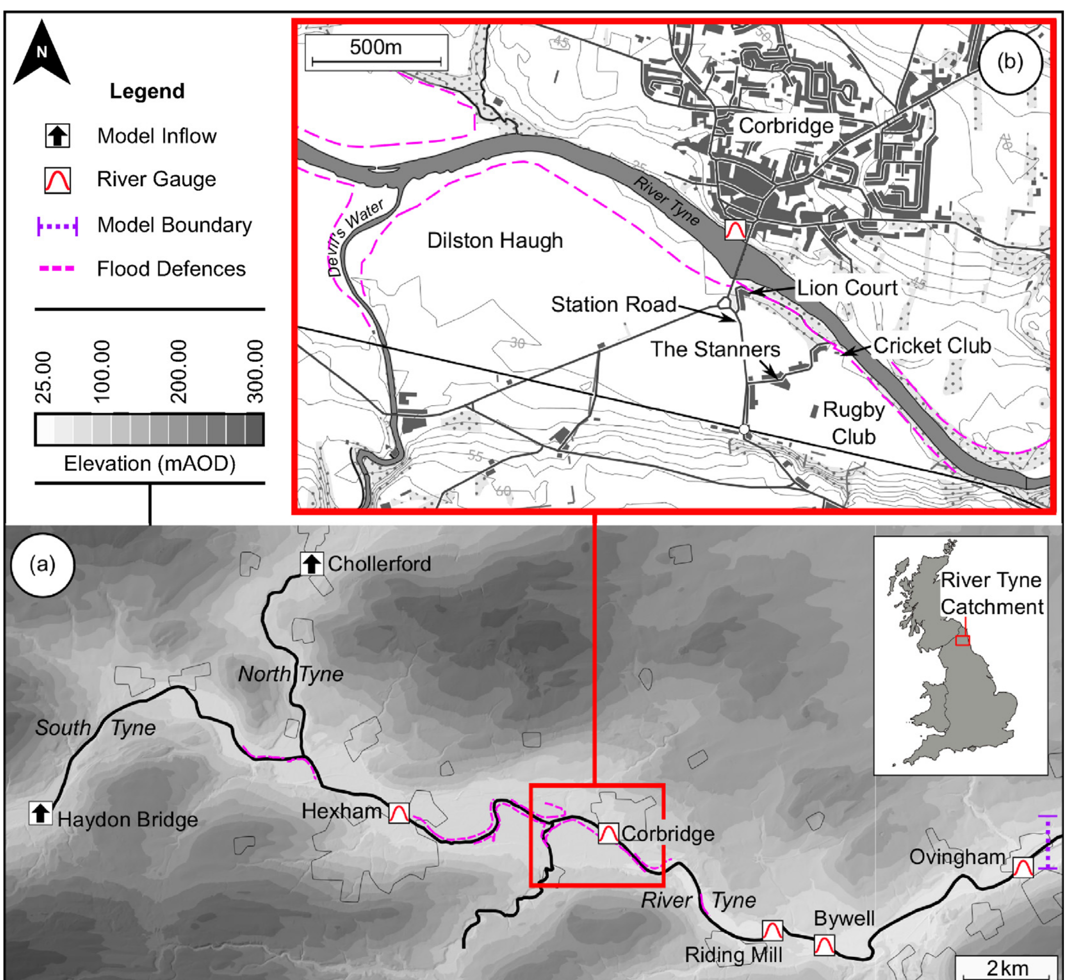

Fig. 1. (a) The modelled reach showing the key elements of the model and the locations of the boundary conditions used. (b) the Corbridge study area and locations referred to in the text.

Table 2
VGI data used for reconstruction of the December 2015 flood event. Data was collected between April and May 2016.

Data Type	Source	Quantity
Personal accounts	• Interviews and correspondence with individual members of the Corbridge Flood Action Group	5
Mapped data	• Group mapping workshops undertaken with members of the Corbridge Flood Action Group	Outputs from two group mapping workshops
Photographs	• Photographs taken during or immediately after the flooding event showing flood pathways or impacts, e.g. areas of gravel deposition or wrack lines, contributed by members of the Corbridge Flood Action Group	18
	• Photographs taken after the event by the researchers showing impacts e.g. wrack lines	
Video	• Videos taken during the flood event by members of the Corbridge Flood Action Group	2
	• Videos taken by UAV immediately after the flooding event and obtained through correspondence with research participants.	2 – one taken 24hrs after the peak of the flood and one 48hrs after the peak of the flood

3. *Timeline* – data which provided information on the timing of key events during the flood, including overtopping of defences, arrival of flood water at key locations, and inundation of properties.

Mapped data and personal accounts (anecdotal data) were combined into a single vector layer within a GIS, with the anecdotal data included within the layer as specific or linked attribute data following the qualitative GIS approaches of Cope and Elwood (2009). This layer was used to reconstruct a unified account of the event dynamics, including times of overtopping and inundation of properties. Photographs and videos were georeferenced and quantitative information was extracted where possible, for example the location of wrack or height of flood marks, or the direction of gravel deposition showing flow pathways. Where quantitative data was not collected directly, images were used simply for interpretation and to validate other data sources. Perks et al. (2016) have demonstrated how georeferenced UAV data can allow precise quantification of flood flows and flow vectors for an urban situation in Scotland. However, the UAV footage collected during the Corbridge study was obtained opportunistically and as a result did not contain the necessary metadata or ground control point information to allow it to be georeferenced. It was thus used in an analytical manner: using darker surface colours or isolated water bodies to indicate previous areas of inundation (Renschler and Wang, 2017). In areas where no footage was available, interpolation of the flood extent was undertaken based on expert judgement and using LiDAR topography.

3.3.3. *Quality control of VGI data*

The VGI dataset collected for this study is fragmentary and 'format-messy'. This makes the assessment of data quality using traditional quantitative measures difficult. However, it is still necessary to assess the extent to which we can have confidence in the data and the flood event reconstruction derived from it and, to do this, we adopted the approach of Mays and Pope (2000). This validation approach uses a researcher-led, reflexive approach relying on triangulation of different data sources to assess and validate individual pieces of information; for example the comparison of anecdotal accounts with imagery or physical evidence on the ground. This approach does not provide the quantifiable analysis of error normally required for model validation. Instead, the method identifies areas of error and uncertainty (spatial and temporal), or contested knowledge which can arise due to the nature of the VGI data being used.

3.3.4. *The experimental framework for model validation*

The experimental validation brought together the flood event reconstruction derived from the VGI database with the outputs of the LISFLOOD-FP model which represent the dynamics of the event. The outputs showed dynamic flood depths and flow vectors, times of inundation, and maximum flood extents.

Flood depths and times of inundation were extracted directly from the model at user-defined time-steps in raster grid format. As a velocity output, the model produces grids representing the flow of water between grid cells in both the x and y directions. To convert these velocity grids into flow vectors, the SAGA GIS tool 'Gradient Vectors from Directional Components' (Conrad et al., 2015) was used. An average across 4 grid cells (40 m) was used to reveal underlying flow directions which could be compared against the observed evidence. Fig. 2 shows the experimental approach and the VGI datasets used to validate the different dynamics of the event.

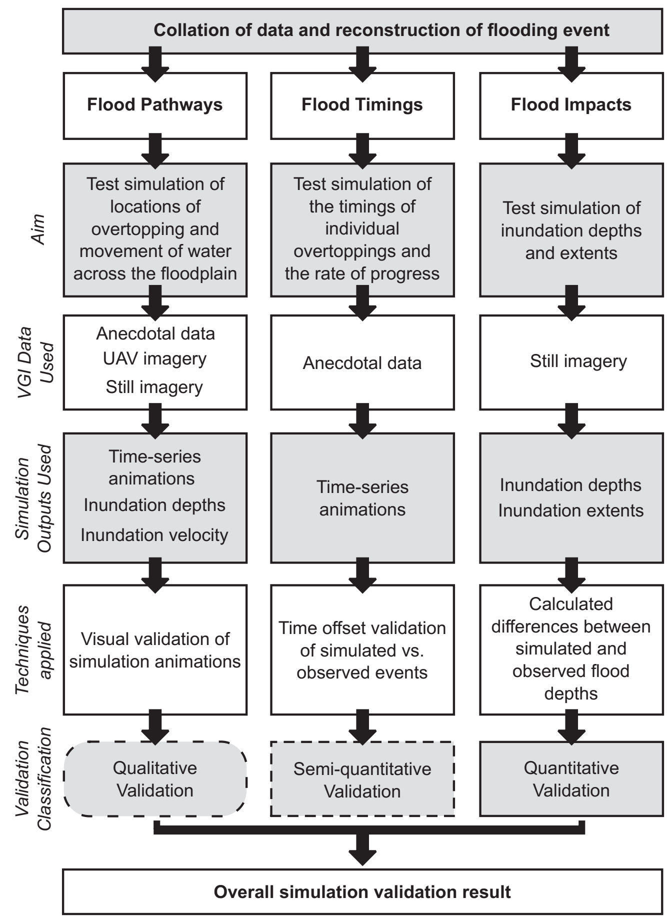

Fig. 2. The experimental approach showing the types of validation which can be applied, depending on the available information and how these correspond to the dynamics of the event. The availability of data and the validation methods adopted influences the nature of the final validation, which represents a blend of qualitative, semi-quantitative, and quantitative data and methods.

4. Results

4.1. *Calibration and validation of the model outputs using established methods*

Table 3 shows that the model performed consistently well in

Table 3
Results of the calibration and validation of the model using standard statistical techniques. Emboldened and highlighted rows indicate the best performing parameter sets which were used to estimate the parameters for the final model. The calibrated model used Manning's n of 0.03 ($m^{1/3}s^{-1}$) on the floodplain and 0.04 ($m^{1/3}s^{-1}$) in the channel, and a DEM resolution of 10 m.

Parameter Tested			RMSE				NSE (vs Gauge)				C%
			Hexham	Corbridge	Riding Mill	Bywell	Hexham	Corbridge	Riding Mill	Bywell	
	Channel	Floodplain									
Mannings '*n*'	0.02	0.03	0.519	0.823	0.818	0.725	0.774	0.773	0.744	0.851	76%
	0.02	0.04	0.519	0.823	0.818	0.725	0.774	0.773	0.744	0.851	76%
	0.02	0.05	0.519	0.823	0.818	0.725	0.774	0.773	0.744	0.851	76%
	0.02	0.06	0.519	0.823	0.818	0.725	0.774	0.773	0.744	0.851	76%
	0.02	0.07	0.519	0.823	0.818	0.725	0.774	0.773	0.744	0.851	76%
	0.03	0.03	0.235	0.407	0.370	0.247	0.953	0.944	0.948	0.983	90%
	0.03	0.04	0.354	0.590	0.501	0.385	0.895	0.884	0.904	0.958	89%
	0.03	0.05	0.354	0.590	0.501	0.385	0.895	0.884	0.904	0.958	89%
	0.03	0.06	0.332	0.538	0.456	0.338	0.907	0.903	0.920	0.968	89%
	0.03	0.07	0.319	0.508	0.430	0.312	0.915	0.914	0.929	0.972	89%
	0.04	**0.03**	**0.259**	**0.444**	**0.334**	**0.191**	**0.944**	**0.934**	**0.957**	**0.990**	**90%**
	0.04	0.04	0.233	0.365	0.422	0.332	0.954	0.955	0.932	0.969	90%
	0.04	**0.05**	**0.259**	**0.444**	**0.334**	**0.191**	**0.944**	**0.934**	**0.957**	**0.990**	**90%**
	0.04	**0.06**	**0.259**	**0.444**	**0.334**	**0.191**	**0.944**	**0.934**	**0.957**	**0.990**	**90%**
	0.04	**0.07**	**0.259**	**0.444**	**0.334**	**0.191**	**0.944**	**0.934**	**0.957**	**0.990**	**90%**
	0.05	0.03	0.227	0.365	0.365	0.267	0.957	0.955	0.949	0.980	90%
	0.05	0.04	0.227	0.365	0.365	0.267	0.957	0.955	0.949	0.980	90%
	0.05	0.05	0.235	0.348	0.466	0.393	0.954	0.959	0.917	0.956	86%
	0.05	0.06	0.227	0.365	0.365	0.267	0.957	0.955	0.949	0.980	90%
	0.05	0.07	0.319	0.508	0.430	0.312	0.915	0.914	0.929	0.972	89%
	0.06	0.03	0.238	0.343	0.500	0.437	0.952	0.961	0.904	0.946	90%
	0.06	0.04	0.238	0.343	0.500	0.437	0.952	0.961	0.904	0.946	90%
	0.06	0.05	0.238	0.343	0.500	0.437	0.952	0.961	0.904	0.946	90%
	0.06	0.06	0.238	0.343	0.500	0.437	0.952	0.961	0.904	0.946	90%
	0.06	0.07	0.238	0.343	0.500	0.437	0.952	0.961	0.904	0.946	90%
DEM Resolution	5		0.093	0.436	1.271	0.761	0.993	0.936	0.381	0.836	88%
	7.5		0.220	0.435	0.341	0.710	0.959	0.937	0.956	0.857	88%
	10		**0.288**	**0.487**	**0.443**	**0.320**	**0.930**	**0.920**	**0.925**	**0.971**	**89%**
	20		**0.204**	**0.261**	**0.359**	**0.514**	**0.965**	**0.977**	**0.951**	**0.925**	**89%**
			RMSE				NSE				C%
			Hexham	Corbridge	Riding Mill	Bywell	Hexham	Corbridge	Riding Mill	Bywell	
Calibrated Model (Mannings '*n*' FP 0.03 Ch 0.04 / DEM resolution 10m)			0.259	0.443	0.335	0.194	0.944	0.934	0.957	0.989	90%

simulating gauged water levels along the whole modelled reach with a floodplain Manning's *n* of between 0.03 and 0.07 ($m^{1/3} s^{-1}$) and a DEM resolution of either 10 or 20 m. This DEM resolution is in line with the recommendations of the UK Environment Agency Fluvial Design Guide (Crower, 2009), which suggests model resolutions of 25 m in rural areas and 10 m for urban areas. It is also in line with other catchment or sub-regional studies, although there is significant variation in the resolutions used (Gobeyn et al., 2017; Neal et al., 2011; Renschler and Wang, 2017; Savage et al., 2016; Wing et al., 2017). Some studies have demonstrated the use of very high resolution topographic information, for example Sampson et al. (2012), but these are exclusively applied to small scale, urban studies rather than the larger, rural reaches such as that simulated in the current study.

Table 3 also indicates the goodness of fit, measured by the Critical Success Index *C*, between the simulated and observed maximum flood extents within the study area. The results indicate that all of the tested parameter sets achieved greater than 85% success in matching the observed peak flood extents. The calibrated model achieved a 90% success rate, which compares very favourably with other modelling studies which achieved between 50% and 90% success rates (Renschler and Wang, 2017; Wing et al., 2017). At a local scale, visual assessment of the simulated and observed extents (Fig. 3) show that within the area of interest there was considerable variability in areas of over- and underestimation. In particular, the model overestimated the extent of overtopping of the flood defences at Dilston Haugh (Fig. 3 location a) and at the Rugby Club (Fig. 3 location b), whilst it underestimated the extent of flooding on Dilston Haugh. It is considered likely that the bare earth DEM (vegetation and buildings removed) used in the model contained inaccuracies which influenced the flow of water across the floodplain, which will be discussed further below.

4.2. Application of the experimental validation approach

4.2.1. Reconstruction of the 2015 event dynamics

Fig. 4 shows the reconstruction of the dynamics of the December 2015 flood, undertaken using the VGI database. These can be divided into two types of dynamics: pathways of defence overtopping; and pathways of flow across the floodplain. The results indicated three pathways of defence overtopping (FP1, FP3, and FP4). FP1 and FP3 represented generalised overtopping of the defences (the extent of which is indicated on Fig. 4), whereas FP4 was identified as a specific location of overtopping at the junction between two defence types, which resulted in a distinct flow of water onto the Cricket Club from the north.

Two pathways of flow across the floodplain were also reconstructed. FP2 represented a general flow from the upstream areas of overtopping following the topography of the floodplain. FP5 represented backing up of water that was unable to return back to the river as a result of the flood defence and the high water levels in the river. This was manifested in the data as a reported sudden increase in depth at properties between 19:00 and 20:00 GMT on 5th December. Two main areas of impact were also represented at The Stanners (Fig. 4, FI1) and Station Road (Fig. 4, FI2). Although the distribution of properties affected by the flooding event was greater than that shown, no data was available

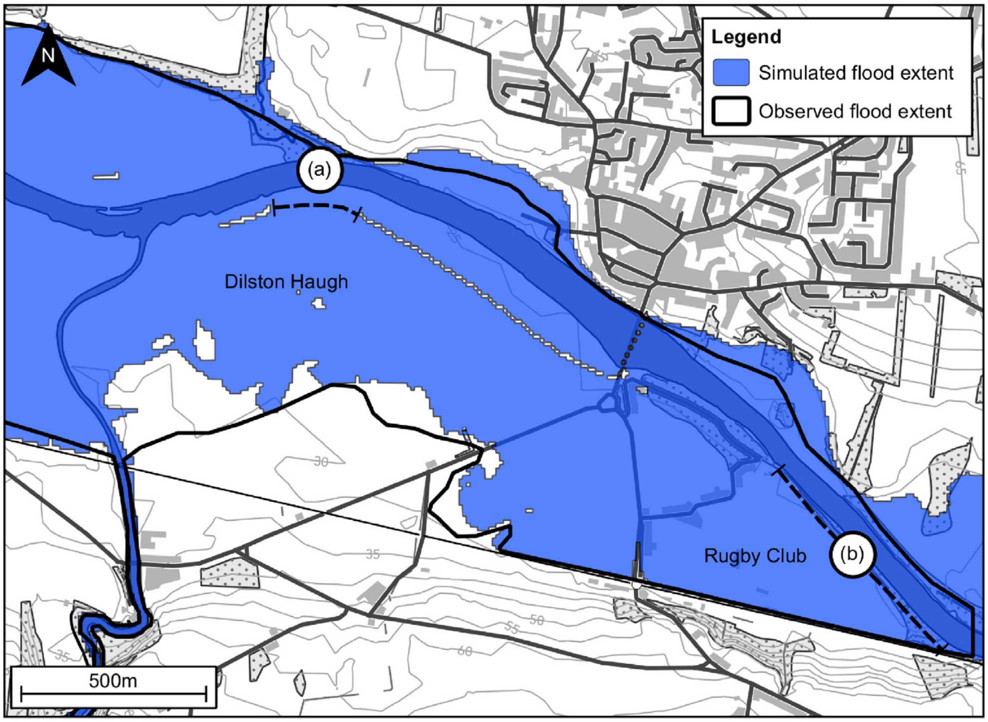

Fig. 3. The predicted maximum flood extent produced by the calibrated model compared to the observed maximum extent derived from analysis of the UAV imagery. The results show that there was some variability in the under- and over-prediction of flooding on both banks. In particular, locations (a) and (b) showed areas of overtopping of the defences which were not observed, indicating that the bare earth DEM used for the model may contain inaccuracies which affected the flow of water across the floodplain.

to validate the impacts in these other areas.

4.3. Results of the experimental validation

The calibrated model was validated against the key pathways, timings and impacts of the December 2015 flood identified in Section 4.2.

4.3.1. Validation of flood pathways

Pathways were identified from the model simulation using 15 min resolution time-series outputs of depth and velocity. Fig. 5 shows the results of the validation. The results indicate that the model was successful in simulating all of the major pathways identified in the observed data. In the case of FP1 and FP2 the model showed general overtopping of the defences along Dilston Haugh and flow following low-lying areas of the floodplain topography, which are potentially relict river channels. This is further north on the floodplain than was interpreted from the VGI, and is considered to reflect error within the VGI rather than in the model. This is because these flow pathways were not directly observed by the research participants; instead they were inferred from the direction of flood waters which entered their homes. For FP3 and FP4 the model showed successful differentiation between the two pathways. FP3 was simulated as overtopping of the wall at Lion Court, and there is also a distinct overtopping location at FP4. This results in flow across the Cricket Club from the north, reported by research participants, which is separate to the other flooding at and around Lion Court.

The processes behind the time-line of FP5 were the most contested within the VGI, with participants reporting a sudden increase in depth at The Stanners and Station Road (Fig. 5), but with considerable disagreement over the pathway this water had taken. Review of the flow vectors produced by the model for this area was not conclusive in identifying a simple backflow of water. However, calculation of the change in simulated inundation depth at The Stanners does show a significant increase in depth in the area which corresponds to the observed pattern and timing of flooding. This suggests that the model is accurately simulating the observed flooding situation. However, whether or not the processes underlying this simulation are accurate, cannot be validated with the available data.

4.3.2. Validation of flood timeline

The success of the model at simulating the timings of the December 2015 flood was assessed based on the 15 min resolution time-series animations produced by the model. Table 4 shows the simulated timeline against the observed timings and demonstrates that the model was successful at predicting the timings of pathways FP1-4 as it simulated the pathways in the observed order, and either at the correct time, or within the time-periods identified by participants. In simulating FP5, the model showed a significant increase in depth in these areas from 18.30 GMT onwards (Fig. 5) where it showed a 30 min offset from the observed time. However, it is also possible this offset reflected variation in the timing of the effect observed by participants rather than any error in the model itself.

4.3.3. Validation of flood impacts

Section 3 has already outlined the partial validation of the flood extents of the 5th December 2015 flood event, which demonstrated that the model achieved 90% global accuracy in simulating maximum flood extent and water levels. However, the simulation of local water levels (and hence flood depth) can also be assessed using quantitative data on flood levels derived from imagery obtained across the area of interest. Eighteen images were collected as part of the research that could be used for the validation. Of these, 12 were capable of being used for validation of flood impacts, with 4 located along the Dilston Haugh flood defence, two each at the Stanners and Station Road, and three at the Cricket Club (Fig. 5), providing coverage of the majority of the study area. Eight of these images provided information on the maximum flooded depth and could be used to quantify the variation in observed and simulated depths. Four images did not provide any direct information on maximum depths, but provided a minimum constraint to simulated maximum depths as they showed inundation depths on Sunday 6th December, on the waning limb of the flood hydrograph.

Table 5 shows that there was variable success in the simulation of local flood depths. Along the flood embankment at Dilston Haugh (Table 5, photographs 1–5), the model consistently underestimated flood depths overtopping the flood embankment by an average of

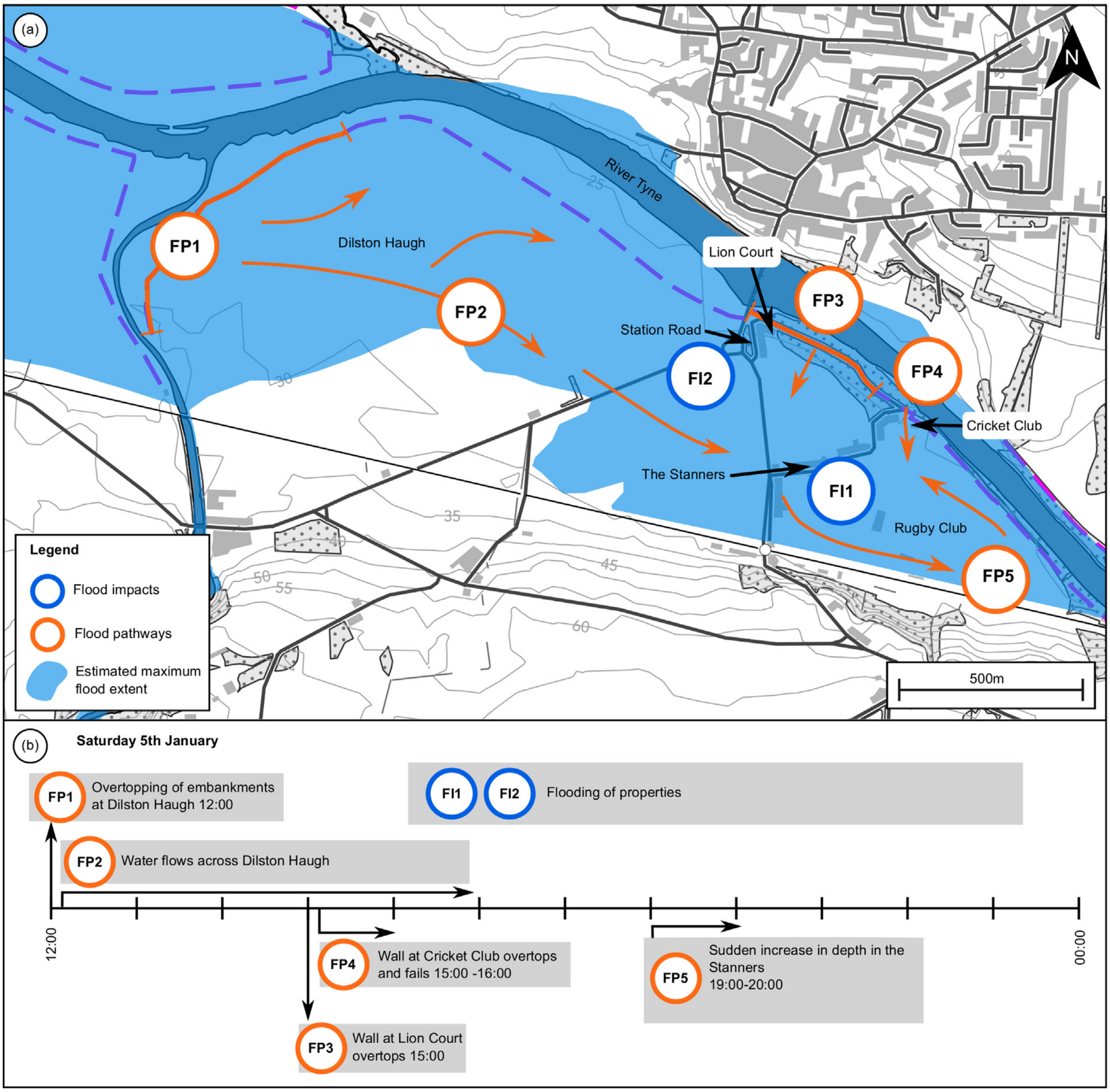

Fig. 4. Reconstruction of the (a) spatial distribution of flood pathways and impacts, and (b) timings, of the December 2015 flood using the VGI database. Pathways are referenced in order of occurrence. The reconstruction indicated three principle areas of overtopping, with two main pathways across the floodplain and two main areas of impact. The flood timings indicated that water began to overtop the Dilston Haugh defences at approximately 12:00 GMT on the 5th, with the overtopping of the Lion Court and Cricket Club defences occurring later. The sudden increase in flooding between 19:00 GMT and 20:00 GMT represented the backing up of flood waters from the Rugby Club as part of FP5.

0.25 m and up to a maximum of 0.50 m. At The Stanners and the Cricket Club (Table 5, photographs 8, 9 and 12) the model was more successful, with the difference between interpreted and simulated depths of only 0.02 m and 0.16 m respectively. For those images which provided only a minimum constraint to the simulated depths, the modelled depth exceeded the minimum constraint in all cases. These results suggest that there were disparities in the way that the model simulated the flow of water into and/or out of the study area. The underestimation of depths along the Dilston Haugh defences suggested that this pathway was not correctly simulated, with too little flood water overtopping the defences at this location. That local flood depths at The Stanners and the Cricket Club were more accurate suggesting that overtopping at this location might be too great. These results were substantiated by the maximum extent results (Fig. 3), which showed overtopping of the embankments at the Rugby Club, something not reported in the VGI database. Taken together, these results demonstrated that, at a local scale, simulation of inundation depths and extents was quite variable. This was despite the model showing high levels of accuracy at a global scale. These results likely reflect inaccuracies in the bare earth DEM which influenced simulated flow at a local scale. These inaccuracies could potentially have been introduced either during the pre-processing filtering process or during the resampling of the data from 2 m to 10 m resolution.

5. Discussion

This paper has introduced a new approach to flood model validation. The approach uses a VGI database collected during and immediately after a severe flood event to reconstruct and validate event dynamics. This approach builds on traditional, statistical approaches which are typically spatially or temporally limited and do not give a full picture of how an inundation model is performing at a local scale. The approach has been tested using a VGI database collected following a

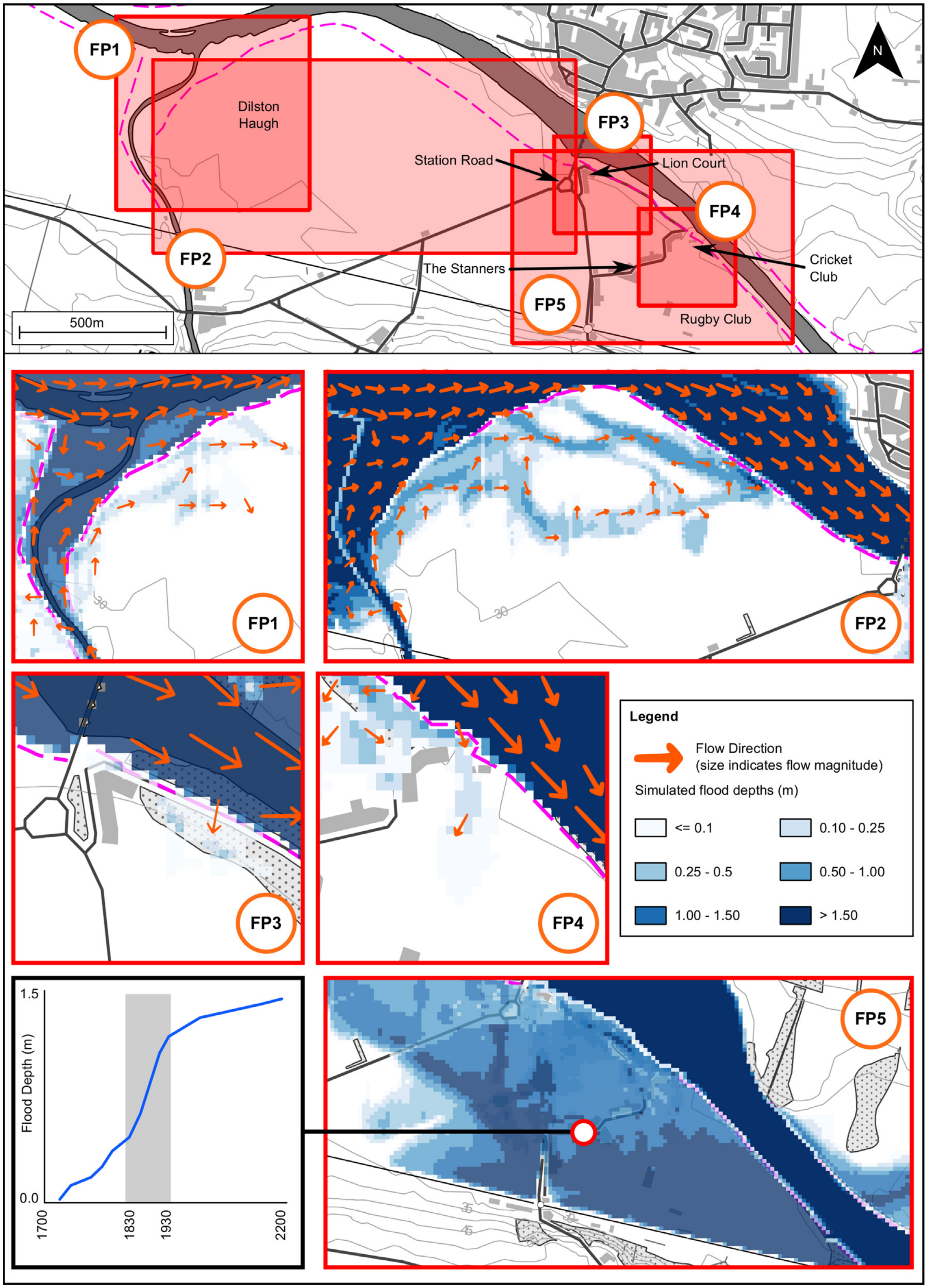

Fig. 5. Simulation results used for the validation of flood pathways. Validation was undertaken dynamically using GIS but for the purposes of static display results are extracted from the model for the time which corresponds with the flood pathway being demonstrated. FP5 shows flood depth change through time for the location on The Stanners indicated in the inset map and the graph highlights the rapid increase in depth shown by the simulation between 18.30 GMT and 19.30 GMT, corresponding with the conditions reported by research participants.

Table 4
Results of the validation of Flood Timings showing that the model was, in the majority of cases, able to accurately simulate both the relative order of events and also their specific times reported by participants.

Pathway	Observed time (GMT)	Simulated time (GMT)
FP1	12:00	12:00
FP2	12:00 onwards	12:00 onwards
FP3	15:00 – 16:00	15:30
FP4	16:00 – 17:00	16:30
FP5	19:00 onwards	18.30 onwards

severe flood which occurred at Corbridge, UK in December 2015.

5.1. Evaluating the success of the experimental validation method

The results of the research demonstrate that the experimental approach offers a more comprehensive validation of event dynamics than offered by traditional statistical approaches. At a global scale, established quantitative validation methods were used to assess the goodness-of-fit between simulated and observed water levels at river gauges, and between observed and simulated maximum flooded extents. The simulation shows RMSE values of < 0.5 and NSE values of > 0.9 at all available gauges, and a 90% accuracy in simulating the observed maximum extents. This is equal to or better than other similar modelling studies using LiSFLOOD-FP (Renschler and Wang, 2017; Wing et al., 2017), and suggests that the model is successfully simulating the inundation seen during the December 2015 flood event.

However, these established metrics only provide an incomplete, spatially and temporally limited, validation of the model performance (Hunter et al., 2007). The results of the experimental method outlined indicate that the more comprehensive validation is able to identify areas of model under-performance not identified by established global statistical approaches. In particular, the experimental validation shows that, although the model accurately simulates the timeline and locations of flood pathways, it incorrectly simulates the processes of overtopping and consequently local inundation depths. These results likely reflect localised inaccuracies in the underlying 10 m resolution DEM used for the model or the need for greater spatial variability in the parameterisation of roughness, both which could influence the flow of water across the floodplain which is not identified at a global scale. This would have potentially serious consequences if the model was to be used for local emergency response planning, or informing, for example, population evacuation strategies (Simonovic and Ahmad, 2005).

5.2. VGI data as an alternative to ‘established’ data sources

Fig. 6 categorises the data used in the study according to its

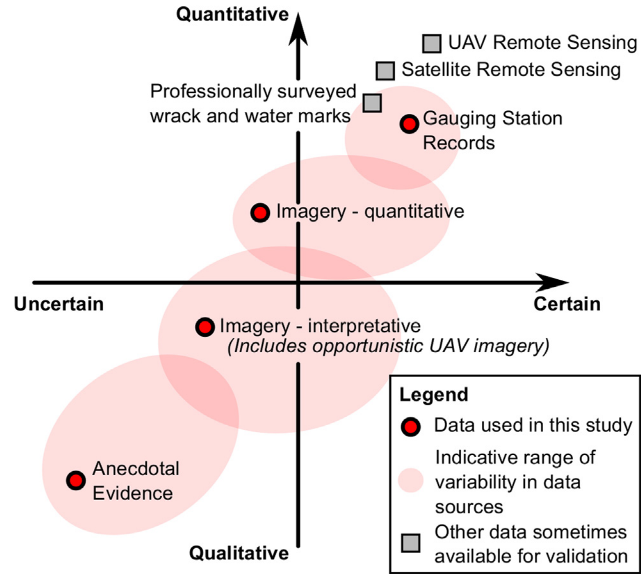

Fig. 6. Categorisation of the VGI datasets collected and used in this study in comparison to established datasets used for model validation. Quantitative imagery are those imagery from which direct quantitative measurements can be made (e.g. wrack marks), whilst interpretative imagery provide non-quantitative indicators (e.g. flow pathways), including opportunistically collected UAV survey data.

qualitative-quantitative nature and its degree of certainty, in comparison to more established data sources. Fig. 6 shows how the VGI data is set apart from traditional data in its range of sources and how it comprises a blend of quantitative, semi-quantitative, and qualitative data. The study demonstrates that this range of data sources makes it possible to understand and reconstruct flood event dynamics using the VGI data as a standalone dataset. As shown through the validation of the flood timeline, and local scale pathways and impacts presented here, VGI data offers opportunities for validating aspects of the flood inundation models at spatial and temporal scales which would be almost impossible using traditional means. This makes VGI a valuable alternative to traditional data sources, not just for immediate post-disaster response and recovery (Haworth and Bruce, 2015), but also as a longer term source of data to inform scientific analysis (Granell and Ostermann, 2016). This range of data sources has also been shown to be important to achieving a valid VGI dataset, particularly where a mixture of qualitative-quantitative data prevents the application of statistical metrics. Previous studies using more single-format databases have highlighted data validity as a limitation of VGI data (e.g. Klonner et al., 2016). However, we have demonstrated the usefulness of adopting a

Table 5
Comparison of spot water levels obtained from photographs with simulated maximum water levels. Photographs representing maximum water levels allow direct comparison with simulated levels. Minimum constraints represent the minimum level of flooding that should be achieved by the simulation.

Number	Location – description	Image category	Interpreted depth (m)	Simulated depth (m)	Difference (m)
1	Dilston Haugh Flood Defence – extent of overtopping and depths above flood	Maximum level	0.4	0.325	−0.075
2	wall	Maximum level	0.4	0.279	−0.121
3		Maximum level	0.5	0.210	−0.29
4		Maximum level	0.3	0.030	−0.27
5		Maximum level	0.5	0.001	−0.499
6	Station Road – flood waters remaining at Station Road roundabout on Sunday	Minimum constraint	0.4	0.826	0.426
7	morning	Minimum constraint	0.4	0.995	0.595
8	The Stanners – maximum water level marks on property walls at property on	Maximum level	1.0	1.019	0.019
9	The Stanners	Maximum level	1.0	1.019	0.019
10	Cricket Club – water ponding within Cricket Club on Sunday	Minimum constraint	1.0	1.594	0.594
11	Cricket Club – water mark on wall shows Sunday level	Minimum constraint	1.0	1.582	0.582
12	Cricket Club – water mark shows maximum depth at club house	Maximum level	1.2	1.362	0.162

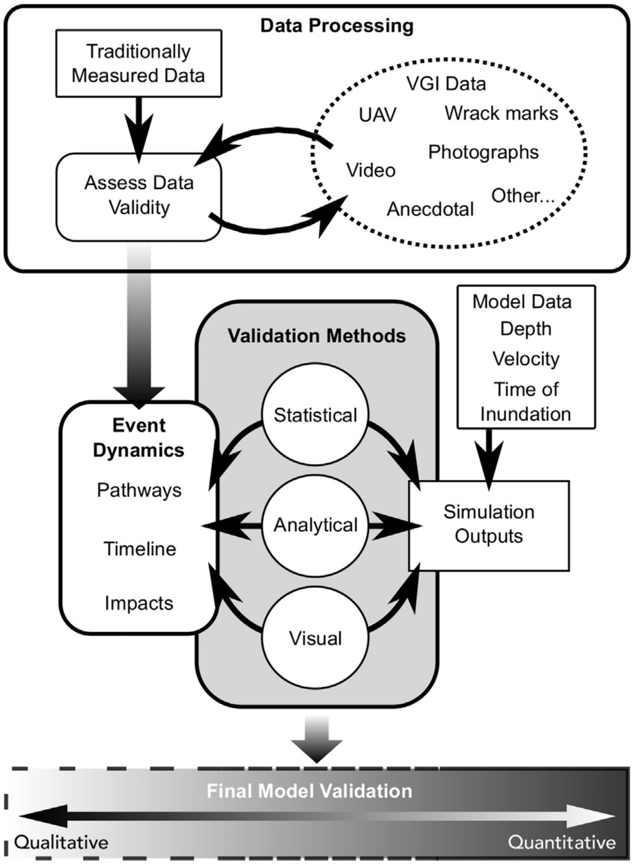

Fig. 7. A new framework for the validation of flood inundation models. The framework reflects the flexibility demonstrated in the study in using non-standard data sources to examine the underlying dynamics of flood events simulated by modern inundation models. The results of the validation reflects the diverse nature of the data and the validation methods which can be applied, and in so doing accepts a reduced quantified rigour in return for achieving a more comprehensive understanding of complex event dynamics.

much more flexible and interpretative model of data assessment based on triangulation with different data sources (Mays and Pope, 2000; Sousa, 2014; Wiggins and He, 2016).

5.3. A new framework for validating flood inundation models

This study has demonstrated a new approach to the validation of flood inundation models, with the aim being simulation of underlying event dynamics through better incorporation of VGI. The study has also demonstrated the usefulness of community-generated, VGI data as a primary input to the future validation of flood models. Building on these findings, we suggest a new framework for the validation of flood models (Fig. 7).

The proposed framework builds on current statistical approaches to validation by recognising the ability of current numerical models to simulate complex event dynamics, and the wider diversity of data which this study has shown to be applicable to model validation. The framework represents a three-stage process:

5.3.1. Data processing

The framework encourages a flexible and researcher-driven approach to assessing data validity which should reflect the data collected in its methods and outcome. As the fields of citizen science and VGI continue to evolve and mature, new practices of data collection and quality assessment will no doubt emerge (Granell and Ostermann, 2016; Hung et al., 2016). Greater standardisation through structures such as Citizen Observatories represent one way in which data collection might be expanded and improved (Lanfranchi et al., 2014; Wehn et al., 2015). Future improvements in personal technology will also likely make UAV data (Perks et al., 2016; Smith, 2015) and geo-located citizen data from personal electronic devices (Newman et al., 2012; Tang et al., 2017) more widely available. Taking these potential future developments into account, the framework aims to encourage the use of a wide range of data in many formats to allow cross referencing and triangulation between data sources.

5.3.2. Event dynamics

The framework proposes *pathways*, *timeline*, and *impacts* as broad categories through which principle event dynamics can be defined. This includes the traditionally assessed metrics of in-channel gauged levels and maximum inundation extents, but recognises that for many uses the parameterisation of numerical models in terms of these metrics alone is overly simplistic. By assessing a wider range of *processes* within the framework we can develop a more holistic validation and ensure that the dynamic simulation capabilities of modern numeric models are exploited to their full potential.

5.3.3. Validation methods

The framework adopts the same flexible approach to the validation of simulated dynamics as to data assessment. This recognises that different input data, simulations, and dynamics require different approaches to validation. Three broad types are proposed: *statistical*, incorporating established performance measures (Wing et al., 2017); *analytical*, reflecting semi-quantitative approaches such as the analysis of UAV footage and quantitative imagery demonstrated by this study; and *visual*, encompassing all techniques which rely on 'on the face of it' validation (Rykiel, 1996). The latter would include the assessment of pathways against the dynamic simulation outputs demonstrated in this study. The balance of validation techniques should reflect both the availability of simulation outputs and the availability of suitable data against which to validate them.

The final validation produced by the framework is a flexible one, influenced by the dynamics of the event, the data available, and methods adopted. The final result will likely lack the quantitative rigour of established statistical methods. Based on the results of this study we propose that some degree of inaccuracy and uncertainty can be accepted in return for the benefit of achieving a more comprehensive understanding of complex flood event dynamics (Granell and Ostermann, 2016). By adopting a more flexible approach to using VGI data in this way we can improve model validation, and, furthermore, open up the currently expert-led practices of flood risk assessment to greater public participation (Usón et al., 2016).

6. Conclusions

Numerical models are the foundation of flood risk assessment and management, used for understanding and mapping areas at risk from floods and planning management interventions. Recent improvements in computing power and model code, and increases in the availability of spatially distributed data on floodplain environments have increased the popularity of 2D models for providing detailed simulations of complex flood dynamics. However, improvements in model simulations have not been accompanied by corresponding improvements in model validation. Due to a lack of data from, during, and immediately after flooding events, validation of flood inundation models still grounded in the statistical assessment of spatially and temporally limited datasets, such as remotely-sensed flood extents or in-channel river gauging. The research presented in this study has demonstrated a new approach to the validation of flood inundation models, using VGI data to provide information on event dynamics not captured by traditionally measured datasets. In so doing, we have demonstrated that:

1. By collecting a wide range of VGI data from multiple sources it is possible to reconstruct in detail the dynamics of a severe flood. Although statistical validation is less rigorous, the quality of this reconstruction can be assessed through data triangulation and other qualitative approaches.
2. The reconstruction of flood pathways, timeline, and impacts of flooding can be used to validate the dynamic outputs of a 2D flood inundation model, and allow both spatial and temporal examination of model performance in simulating flooding processes.
3. The experimental model validation approach tested here enhances existing global statistical approaches to validation by examining the simulation of underlying flood processes using the case study of a large flood on the River Tyne, UK. The results of the test case indicate that a model assessed using traditional methods as having a global accuracy of over 90% in simulating gauged river levels and maximum flood extent does not accurately represent the actual pathways and impacts of the event. This is potentially highly significant when models are used in a dynamic way to plan and assess floodplain management interventions.

Drawing on these conclusions we propose a new, flexible framework for the validation of flood inundation models. In contrast to current approaches, the framework encourages the use of a diverse range of non-traditional data, now and into the future. Similarly, the framework encourages a mixture of approaches to validation to be adopted, leading to more flexibility depending on data availability and aspects of the simulation being considered. Although the final validation may lack the quantitative rigour of established global approaches, it provides a more comprehensive and bespoke examination of the model's performance, particularly for situations where dynamic model outputs are being used to inform potential floodplain interventions.

The results shown by this study also demonstrate the value of alternative data sources such as VGI, or data collected from citizen science programmes, to enhance and extend established data sources. We have demonstrated that many of the common criticisms of alternative data being 'messy' and unscientific can be understood or overcome by relatively simple procedures for quality control such as triangulation. However, data is, as demonstrated by other studies, not always as diverse or spatially distributed as that collected in this study, a fact that must be considered when translating this approach to other areas. For triangulation to be effective a mixture of overlapping data from different informants and from different sources (e.g. anecdotal, remote sensing, imagery) is essential. Additionally, all of these data need to be located, both spatially and temporally, within the study area or event of interest. This necessitates further research on the development of data collection approaches which combine the locally situated engagement adopted in this study with structured data collection approaches of citizen science or citizen observatories, and the spatial coverage of technology-based VGI approaches.

With predicted increases in the risk of flooding as a result of future climate change, numerical models are likely to continue to represent a significant asset in flood risk assessment practices. The VGI framework proposed here represents a more comprehensive process of model validation based on the more effective use of alternative data sources. This has the benefit of both allowing more comprehensive exploitation of modern numerical modelling to better simulate complex river-floodplain interactions and also encouraging the exploration and use of diverse datasets which may open up new perspectives on the use of numerical models for the creation flood risk knowledge. To effectively integrate the proposed validation framework into future modelling work, further research is urgently required in order to explore how technological VGI solutions could be developed to allow the routine collection of flood data through local engagement platforms such as citizen observatories.

7. Declarations of interest

None.

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